Bangor Business School Working Paper

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BBSWP/09/004

EFFICIENCY AND RISK-TAKING IN EUROPEAN BANKING

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December 2009

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Abstract

The recent period of crisis in credit markets has highlighted the crucial role of bank risk taking. Our paper assesses the inter-temporal relationships among bank efficiency, capital and bank risk-taking in the EU-26 commercial banking industry between 1995 and 2007. Our results support the bad management-, luck-, cost and revenue skimping hypotheses. Overall, our paper provides evidence that higher performance (enhanced efficiency) has been not related to higher managerial skills, rather to cost and revenue skimping and bad management.

Keywords: banking risk; capital; efficiency

JEL classification: G21; D24; C23; E44

[1] Special thanks to Alessandro Carretta, Francesco Cesarini, Barbara Casu, John Fell, E.P.M. Gardener, Claudia Girardone, Hans-Joachim Klöckers, Marcella Lucchetta, Adrian van Rixtel, Roberto Violi, John Wilson and Giuseppe Zadra who kindly provided comments on versions of this paper as well as participants at seminars at the European Central Bank and Banca d'Italia. We are also particularly grateful to Badi Baltagi for his comments on the estimation procedures. Finally, we are grateful to Gabe De Bondt, Claudia Girardone, Raymond Desmonts and Gaby Hebers for excellent help with selection and discussion of our bank sample. Also thanks to comments from participants at the ABI Einaudi Workshop on European Bank Competition held at ABI Piazza del Gesu 49, 18 September 20009, Rome. All errors and omissions as usual rest with the authors. The financial support of the Istituto (formerly, Ente) Luigi Einaudi, sponsoring the research project "Competition in European Banking" is gratefully acknowledged

Efficiency and risk-taking in European banking

1. Introduction

Over the last two decades, European banking markets have become increasingly integrated. This progressive process of financial integration has enhanced competition and emphasised the importance of improved efficiency. That is, it is forcing banks closer to the “best practice” or efficient production function. At the same time, this increase in competition could – at least in the short term – lead to greater (and possibly excessive) risk-taking by banks. This is because increased competition reduces the market power of banks thereby decreasing their charter value. The decline in banks´ charter values coupled with the existence of limited liability and the application of flat rate deposit insurance could encourage banks to take on more risk (Matutes and Vives, 2000 and Salas and Saurina, 2003)[2]. Regulators have tried to counterbalance these possible incentives by giving capital adequacy a more prominent role in the banking regulatory process.[3]

Paradoxically, the abundant theoretical literature on the relationship between banks´ risk and capital requirements often yields conflicting predictions (Berger et al., 1995, Jackson, 1999).[4] In this respect, Hellman, Murdock and Stiglitz (2000), and Besanko and Kanatas (1996) showed that higher capital requirements might induce excessive risk-taking by banks. This is because higher capital requirements would reduce the banks´ charter value thereby

[2] This issue is not undisputed; Boyd and Nicolo (2003) argue that the theoretical foundations linking more competition with increased incentives towards bank risk-taking are fragile. See Carletti and Hartmann (2002) for a useful survey of the literature linking competition and stability.

[3] For instance Vives (2000, pg. 15) *‘the general trend is to introduce competition in banking and to check risk- taking with capital requirements and appropriate supervision’*.

[4] On the other hand, there is almost a consensus that capital adequacy regulations should be set up in conjunction with other prudential regulatory instruments in order to create an optimal set of incentives (see for instance Freixas and Gabillon, 1998, Vives, 2000, Santos, 1999 and Marshall and Prescott, 2000).

limiting banks´ incentives to behave prudently. On the other hand, Repullo (2004) argued that risk-based bank capital requirements are in general effective in preventing banks from taking excessive risks. The main reason for these contradictory results is that most of the hypotheses are non-exclusive. For instance, agency and information asymmetry problems may have a significant impact on trade-offs between banks´ risk and capital positions. This explains why some institutions may react to increased capital requirements by taking additional risks, while others may reduce leverage. Against this background, we aim to assess the intertemporal relationships among bank efficiency, capital and bank risk-taking[5] in the EU-26 commercial banking industry between 1995 and 2007 by using Granger-causality tests (Berger and De Young 1997, Williams 2004) as well as introducing revenue and profit efficiencies and also various detailed bank risk measures (e.g. Moodys and EDF estimates from Moodys-KMV).

2. Related literature

There is an early line of US research on bank risk-taking incentives that examined the effect of capital regulations on bank behaviour (.e.g. Peltzman, 1970 or Mayne, 1972).[6] The main concern of these early studies was to analyse the effectiveness of financial regulation and, especially, to consider whether the existence of a flat-rate deposit insurance created incentives for excessive risk-taking by bankers. The introduction of new additional capital adequacy regulation was expected to force financial institutions to hold an amount of capital adequate to the amount of risk taken by individual institutions. Overall, results from these earlier studies were sceptical about the

[5] See reviews by Berger et al., (1995) and Jackson (1999).

[6] Most of these earlier models are based on Friedman’s (1962) capital adjustment model.

effectiveness of banking capital regulation influencing banks' target capital ratios. Instead, these studies emphasised the importance of other determinants of bank capital, such as the structure of deposit insurance and/or the level of nominal interest rates (see Marcus, 1983). The theoretical literature offers contradictory results as to the optimal design of capital adequacy regulation and to the effects of capital requirements on bank risk-taking incentives (see Berger *et al.*, 1995; Freixas and Rochet, 1997; Santos, 1999; Boot *et al.*, 1998; Rime, 2001). The issue of how higher capital ratios reduces overall banking risk has largely been unresolved in the literature. The introduction of the 1988's Basel Accord on international bank capital standards (Basel I) reignited interest on the effectiveness of bank capital regulations. The new wave of studies focused again mostly on the US banking sector[7] and tended to find that regulatory capital constraints are important in influencing the financing decisions made by a significant subset of banks (e.g. Wall and Peterson, 1987 and Dahl and Shrieves, 1990). In the aftermath of the Basle I application and subsequent amendments, the interest on the effects of capital adequacy regulations on banks´ risk-taking persisted. For instance, Shrieves and Dahl (1992) and Ediz et al., (1997) found that bank capital regulation had been effective in increasing capital ratios without substantially shifting bank portfolios and off-balance-sheet (OBS) exposures towards riskier assets in the US and UK. At the same time, Demsetz et al., (1996) and Salas and Saurina (2003) found that banks with lower capital tend to operate with higher levels of credit risk. Building on the predictions of the theoretical literature, a number of empirical studies have also considered the role of bank charter values as a prominent element affecting banks´ incentives towards risk-taking. In this respect most US and European studies tend to find that charter value and bank risk-taking are negatively correlated suggesting that a

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[7] For exceptions using non-US data see Carbo (1994) or Barrios and Blanco (2003).

lower charter value might induce banks to take on more risk (see Keeley, 1990, Saunders and Wilson, 1996 or Gropp and Vesala, 2001).

Hughes and Moon (1995) and Hughes and Mester (1998, 2009) also point out the need to consider bank efficiency in analysing capital and risk relationships since the latter are likely to be simultaneously determined by the level of efficiency. Namely, supervisory authorities may allow efficient banks (with high quality management) a greater flexibility in terms of their capital leverage or overall risk profile, *ceteris paribus*. On the other hand, from a moral hazard point of view, a less efficient bank may be tempted to take on higher risk to compensate for lost returns. Following this view, Berger and De Young (1997) and Kwan and Eisenbeis (1997) argue that due to the central role of banks´ efficiency influencing banks´ behaviour it is useful to recognise explicitly the concept of bank efficiency in the empirical models analysing the determinants of banks´ risk. Although both papers have similar research goals, the research design differs: Berger and De Young (1997) employ Granger-causality methods to assess the intertemporal relationships among problem loans, cost efficiency, and financial capital in US banking between 1985 and 1994. Kwan and Eisenbeis (1997) use a simultaneous equation framework to test hypotheses about the interrelationships among bank interest rate and credit risk-taking, capitalization, and operating efficiency. Both papers provide evidence that both efficiency and capital are relevant determinants of bank risk-taking and moral hazard incentives. Namely, Berger and De Young (1997) show that problem loans precede cost efficiency reductions, and cost efficiency precedes problem loan reductions and capital reductions at thinly capitalised banks. Kwan and Eisenbeis (1997) estimate a negative link between bank efficiency and risk-taking supporting the view that poorly performing banks are more vulnerable to risk-taking than high performance banks (and highly capitalised banks are more efficient than thinly capitalised banks). Both papers have recently been replicated in European banking by Williams (2004) and Altunbas et al., (2007). Similar to Berger and De Young (1997), Williams (2004) use Granger-causality techniques to assess the intertemporal relationships among problem loans, cost efficiency, and financial capital (using a sample of European savings banks over the period 1990-1998) finding that poorly managed banks tend to make more poor quality loans. Altunbas et al., (2007) follow an approach similar to Kwan and Eisenbeis (1997) and use a simultaneous equation framework to investigate the relationship between capital, risk and efficiency (using a sample of European banks over the period 1992-2000) and finding that inefficient banks hold more capital and are less risky than efficient banks. Overall, results for European banks seem to substantially differ from those in the US.

3. The risk-taking, capital and efficiency relationships: research hypotheses

Following Berger and De Young (1997) and Williams (2004), we posit some research hypothesis regarding the relationship among risk-taking, capital and efficiency. Namely, by including new factors (such as revenue efficiency, profit efficiency and various 'new' risk measures), we are able to posit new (not mutually exclusive) hypotheses[8] as follows:

1) the "bad luck" hypothesis posits that an exogenous increases in bank risk-taking temporally precedes a cost efficiency decrease (due to extra-expenses associated with problem loans) so that banks have to purchase

[8] Berger and De Young, (1997) posit four hypothesis: 1) the "bad luck" hypothesis, i.e. an exogenous increases in nonperforming loans temporally precede a cost efficiency decrease so that banks have to purchase additional inputs necessary to administer these problem credits; 2) the "bad management" hypothesis, i.e. a poor cost efficiency temporally precede an increase of nonperforming loans so that banks have to purchase additional inputs necessary to administer these problem credits; 3) the "skimping" hypothesis, i.e. a trade-off between short-term operating costs and future loan performance problems; 4) The "moral hazard" hypothesis, i.e. low financial capital temporally precede high nonperforming loans.

additional inputs necessary to administer the higher risk levels;

2) The “revival” hypothesis posits that an exogenous increases in bank risk-taking temporally precedes a cost efficiency increase (e.g. by recognising possible future problems, banks are able to face the higher risk by cutting waste) so that banks have to purchase additional inputs necessary to administer the higher risk levels;
3) the “luck” hypothesis posits that an exogenous increases in bank risk-taking temporally precedes a revenue efficiency increase (due to extra-income associated, say, with higher interest rates charged by the banks on lower quality loans). There are no cost efficiency effects so banks are able to generate equity capital (internally) to face higher risk-taking and there is no need to purchase additional inputs.
4) the “bad management” hypothesis posits that poor cost and/or revenue efficiency temporally precedes an increase in risk-taking (e.g. due to inadequate loan underwriting, monitoring, and control by bank managers), so that banks have to purchase additional inputs necessary to administer these problem credits;
5) the “cost skimping” hypothesis posits a trade-off between short-term operating costs and future risk-taking: e.g. a reduced amount of resources allocated to underwriting and monitoring loans would make: a) in the short run, banks appear to be cost efficient and the stock of non-performing loans remains unaffected; b) in the medium and long terms, banks have lower revenue and cost efficiencies and higher risk levels; c) banks have to purchase additional inputs necessary to administer future higher risks.
6) the “revenue skimping” hypothesis posits a trade-off between short-term interest income and future risk-taking: a poor quality portfolio would make: a) in the short run, banks appear to be revenue efficient by earning higher interest revenue; b) in the medium and long terms, banks have higher

credit losses due to the low quality of the loan portfolio; c) banks have to purchase additional inputs necessary to administer future higher risks.

7) the "good management" hypothesis posit that a high cost efficiency temporally precedes an increase in revenue efficiency (e.g. due to careful loan underwriting, monitoring, and control by bank managers) and there is a non-negative impact on bank risk taking, so that banks do not have to purchase additional inputs necessary to administer eventual higher risk.
8) The "luck moral hazard" hypothesis posits that thinly capitalised banks respond to moral hazard incentives by increasing their loan portfolios riskiness (which results in higher non-performing loans on average in the future), this results in enhanced revenue efficiency (due to extra-income associated with higher interest rates being charged by banks on lower quality loans) with no impact on cost efficiency so that banks are able to generate internally equity capital necessary to cover future costs.
9) The "bad luck moral hazard" hypothesis posits that thinly capitalised banks respond to moral hazard incentives by increasing their loan portfolio riskiness (which results in higher non-performing loans on average in the future). This does not result in enhanced revenue efficiency, instead it reduces cost efficiency (due to the extra expenses associated with problem loans) so that banks have to purchase additional inputs necessary to administer these higher risk levels.

4. Methodology

We specify linear models to investigate the casual relationships between bank's risk, capital and efficiency as is found in the established literature. Following Berger and DeYoung (1997) and Williams (2004), we use the Granger-Causality techniques to test our research hypotheses[9]. Despite its limitations[10], Granger-causality techniques have been widely applied in the economic literature (e.g. Amato and Swanson 2001, Bajo-Rubio et al., 2001, Assenmacher-Wesche and Gerlach 2008, Jaeger and Paserman 2008) and also in banking studies (e.g. Berger and DeYoung, 1997, Levine et al., 2000, Williams, 2004, Beccalli 2007, Casu and Girardone 2009) to test unique time-ordered and signed relationships among pairs of independent variables so that the Granger-causality test indicate which hypotheses are generally consistent or inconsistent with the data. The Granger-causality test was originally designed for pairs of lengthy time series recently modified to incorporate panel dynamics (e.g. Arellano and Bond 1991; Holtz-Eakin et al. 1988; Hurlin 2005; and Hurlin and Venet 2001). As such, our Granger-causality model is specified as follows:

$$\begin{aligned}
DR_{i,t} &= f_1(DR_{i,lag}, X-EFF_{i,lag}, \tau-EFF_{i,lag}, CAP_{i,lag}, Z_{j:i,t}) + \varepsilon_{1i,t} \\
X-EFF_{i,t} &= f_2(DR_{i,lag}, X-EFF_{i,lag}, \tau-EFF_{i,lag}, CAP_{i,lag}, Z_{j:i,t}) + \varepsilon_{2i,t} \\
\tau-EFF_{i,t} &= f_3(DR_{i,lag}, X-EFF_{i,lag}, \tau-EFF_{i,lag}, CAP_{i,lag}, Z_{j:i,t}) + \varepsilon_{3i,t} \\
CAP_{i,t} &= f_4(DR_{i,lag}, X-EFF_{i,lag}, \tau-EFF_{i,lag}, CAP_{i,lag}, Z_{j:i,t}) + \varepsilon_{4i,t}
\end{aligned} \qquad (1)$$

where i subscript denotes the cross-section dimension, t denotes the time dimension, DR is the bank's default or credit risk, X-EFF and τ-EFF are the cost and revenue efficiency, respectively, CAP is the equity-asset ratio, Z (j = 1,2…, n) are control variables for factors influencing the capital-risk

[9] Granger's (1969, p. 428) notion of causality states that "… y_t is causing x_t if we are better able to predict x_t using all available information than if the information apart from y_t had been used" and Granger's suggestion to regress x_t on its own lags and a set of lagged y_t has become a standard procedure. If lagged y_t contributes statistically significantly to the explanation of x_t, y_t Granger causes x_t

[10] As any econometric procedure, Granger-testing do not proof the economic causation between two variables, rather produce gross statistical associations indicating consistency or inconsistency with an hypothesis

relationship and $e_{i,t}$ is the random error term. The variable definitions are summarised in Table 1.

<< INSERT TABLE 1 HERE >>

Following Berger and DeYoung (1997) and Williams (2004), we specify a AR(4) process for risk, capital and efficiency variables. Substantial problems arise in the estimation of such a model[11]. The introduction of a lagged dependent variable among the predictors creates substantial complications in estimation since the lagged dependent variable is correlated with the disturbance (even assuming that $\varepsilon_{i,t}$ is not itself correlated) [12]. To solve this problem, we use the system-Generalized-Method-of Moments (GMM) estimators developed for dynamic panel models by Arellano and Bover (1995) and Blundell and Bond (1998) to assess these relationships.[13]

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[11] Various studies used the Granger causality test running OLS regressions (e.g. Berger and DeYoung 1997, Williams 2004, Beccalli 2007) encountering endogeneity problems, while recently the Granger causality was applied to dynamic panel models (e.g. Casu and Girardone, 2009).

[12]In a first order dynamic panel data model (such as $y_{i,t} = \alpha_i + \beta\, \mathbf{x}'_{i,t} + \gamma\, y_{t,t-1} + \varepsilon_{i,t} = \alpha_I + \delta\, \mathbf{w}'_{i,t} + \varepsilon_{i,t}$) none of the standard fixed or random error estimators are consistent. Regarding the fixed error, we regress ($y_{i,t}$ - $\bar{y}_i$) on ($w_{i,t}$ - $\bar{w}_i$), but ($w_{i,t}$ - $\bar{w}_i$) is correlated with ($\varepsilon_{i,t}$ - $\bar{\varepsilon}_i$) because of the inclusion of $y_{i,t-1}$ in $w_{i,t}$. Heuristically, the fixed error estimator of δ is a matrix weighted average of the OLS estimates of δ from running OLS on each group separately. These individual estimators have a finite-sample bias of order T^{-1} and averaging across n of them does not remove this. Regarding the Random Effect estimator, this is a matrix weighted combination of fixed error and random error and they are inconsistent. As such, the random error estimator is inconsistent.

[13] The approach proposed in literature (e.g. Anderson and Hsiao 1981, Holtz-Eakin et al. 1990, Arellano and Bond 1991, Arellano and Bover 1995, Blundell and Bond,1998) is to focus on a differentiated equation, such as $y_{i,t} - y_{i,t-1} = \beta\, (\mathbf{x}'_{i,t} - \mathbf{x}'_{i,t-1})' + \gamma\, (y_{i,t-1} - y_{i,t-2}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1})$. In the differenced equation, however, the errors $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$ are now correlated with the $(y_{i,t-1} - y_{i,t-2})$ so the OLS estimation fails. As such, Anderson and Hsiao (1981) propose two instrumental variable procedures by instrumenting for $(y_{i,t-1} - y_{i,t-2})$ with either $y_{i,t-2}$ or $(y_{i,t-2} - y_{i,t-3})$ which are uncorrelated with the disturbance term $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$, but correlated with $(y_{i,t-1} - y_{i,t-2})$. Arellano (1989) shows that using the lagged difference as an instrument results in an i,t-2 estimator that has a very large variance. Arellano and Bond (1991) and Kiviet (1995) confirm the superiority of using the lagged level as an instrument with simulation results. Arellano and Bond (1991) suggest to use two GMM estimators to gain efficiency by exploiting additional moment restrictions. Arellano and Bond (1991) use all available lagged values of the dependent variables plus lagged values of the exogenous regressors as instruments. Various studies (e.g. Ahn and Schmidt, 1995) noted that traditional first-differenced GMM estimator is inefficient neglecting a lot of information. To face this problem, Arellano and Bover (1995) propose to use GMM to jointly estimate the original level regressions and the first-differenced regressions, where the lagged first-differenced variables are used as instruments in the level regressions, and the lagged level variables are used as

In order to ensure the consistency of the GMM estimator, we use two specification tests to assess: 1) the hypothesis that the error term $e_{i;t}$ is not serially correlated by testing whether the differenced error term is second-order serially correlated; and 2) the validity of the instruments by running the Sargan test (by analyzing the sample analog of the moment conditions used in the estimation process). Failure to reject the null hypotheses of both tests gives support to our model.

5. Variables and data

Measurement error is one of the main problems encountered when assessing bank risk-taking and efficiency. Previous studies (e.g. Berger and De Young, 1997, Williams 2004) focus on the non-performing loan ratio (NPL) as a proxy of credit risk. We use three measures of risk in our analysis: the Moody's KMV Expected Default Frequency (EDF), the 5-year cumulative probability of default (PD_{5Y}) and the traditional NPL\L ratio. These three risk measures have different economic meanings and enable us to have a more comprehensive view of the relationship among risk, capital and efficiency. Both EDF and PD_{5Y} refer to the probability of default (PD) within the short and medium terms (1 and 5 years, respectively) so these account for all risks. Both variables are free from managerial discretion and are estimated through an economic cycle (i.e. PD estimates are long-run probabilities of default which take into consideration upturns and downturns in the economy). The NPL, in contrast, is an accounting measure focussing on credit risk subject to managerial

instruments in the first-differenced regression. Blundell and Bond (1998) and Blundell et al., (2000) showed that simulations suggest that a system-GMM estimator can provide substantial gains in precision and efficiency over the first-differenced GMM estimator. The gains of the system-GMM estimators (Arellano and Bover, 1995) relative to the traditional first-differenced GMM estimator (Arellano and Bond, 1991) occur under two circumstances: first, when the autoregressive parameter is close to unity; and, second, when the number of the time-series observations is moderately small. Since our dataset has many panels and relatively few periods, we use the system- GMM estimators developed for dynamic panel models by Arellano and Bover (1995) discretion and is a point-in-time risk measure (i.e. obtained for short horizons). These three measures are likely to have a different link with bank's equity and efficiency.

Regarding bank efficiency, we estimate both cost and revenue efficiency using the stochastic frontier approach (details are outlined in the Appendix) and the intermediation approach for the input and output definition. While previous studies focus on cost efficiency (e.g. Kwan and Eisenbeis 1997, Berger and DeYoung 1997, Williams 2004, Altunbas et al., 2007) or profit efficiency (Berger and Bonaccorsi 2006), we estimate both the cost and revenue efficiency since: 1) we expect that risk and capital may have different links with revenue efficiency; 2) we prefer to disentangle the profit efficiency into cost and revenue effects to check if there are differences, rather than simply estimating one profit efficiency measure (capturing jointly cost and revenue effects) and then its relationship with bank capital and risk. We also estimate profit efficiency as a robustness check.

In our model, we also control for a large number of factors that may influence the relationship between capital, risk and efficiency. Namely, we include as covariates the following variables: 1) bank income diversification (ID, i.e. the ratio between net non-interest income and net operating income ratio)[14]; 2) bank specialisation (BS, i.e. the proportion of loans over total assets)[15]; 3) banking market structure,: namely, we control for the domestic concentration (using the Herfindahl–Hirschman Index) and the number of credit institutions[16]; 4) bank's asset size (i.e. logarithm of total assets); 5) various macro-economics variables, as proposed in the literature (e.g. Salas and

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[14] Lepetit et al., (2008)

[15] Salas and Saurina (2003)

[16] In their review of studies dealing with the competition-concentration relationship, Berger et al., (2004, page 436) states "researchers specified alternative indicators of competition with fewer endogeneity problems than HHI and CR_n. Some have used the number of firms in the market (since entry and exit generally take much longer to occur than do changes in market shares)". Of course, these two measures are found to be negatively and statistically significantly (at the 1% confidence level) correlated, but the magnitude of the Pearson correlation coefficients (i.e. -0.5027) enable us to exclude substantial multicollineary problems.

Saurina 2003, Maudos and De Guevara 2004, Yildirim and Philippatos 2007, Brissimis et al., 2008). In particular, we take into account economic development (GDP growth) and prosperity GDP per-capita). We also include a demographic variable that may impact on the bank delivery channels (i.e. population density) and money market interest rates (a proxy for the stance of monetary policy)

Regarding our data sample, we focus on commercial banks from EU-26 [17]between 1995 and 2007 with financial information obtained from Bankscope, maintained by Bureau Van Dijk, market information are obtained from Datastream (managed by Thompson Financial Limited), 5-year PDs are from Moodys and EDF estimates from Moodys-KMV. Overall, our sample comprises 2,248 bank observations and is mostly composed of French, UK, German, Italian and Spanish commercial banks (respectively, 14%, 10%, 9%, 8% and 8% of our sample). By selecting an AR(4) process for risk, efficiency and capital variables the number of observations substantially reduce (ranging between 659 and 703).

< < INSERT TABLE 2 HERE > >

Mean cost-, revenue- and profit inefficiency are between 37% and 59%, where pro On average, risk measures show low levels: both EDF and the cumulative probability of default at 5 years are lower than 1% and non-performing loans are less than 3.5% of total bank loans. Non-interest income account on average for the 20% of net operating income and total loans are 77.6% of bank total assets. Most of the value drivers considered exhibit a statistically significant correlation (at least at the 10% significant level), but the magnitude of the estimated coefficients is

[17] In order to increase the sample homogeneity, we omit to consider Luxemburg from the EU-27 countries.

usually smaller than 10% (except two cases, where the coefficients is around 40%) suggesting that our models do not suffer of multicollinearity problems[18].

6. Results

6.1 Results: Credit risk (NPL)

Table 3 reports the results from model (1) using four lags on capital, equity and risk variables where bank risk is measured focusing on credit risk (i.e. the non-performing loans ratio) consistently with previous studies. In the X-EFF model (i.e. $y = x\text{-}ineff$), the sum of all lagged NPL/L coefficients is positive and the sum of τ*-ineff* lags is negative and both coefficients are statistically significant at the 10% confidence level. The lagged coefficients of E/A and *x-ineff* are statistically insignificant at the 10% or less and few control variables (i.e. BS, IR and GDPG) display a statistically significant influence on X-EFF. These results are consistent with the view that, as bank risks increase, x-efficiency decline (due to higher costs to manage bad loans), as predicted by the "bad management" hypothesis.

<< INSERT TABLE 3 HERE >>

In the revenue efficiency model ($y = \tau\text{-}ineff$), the sum of all lagged NPL/L coefficients are negative and statistically significant, the sum of *x-ineff* lags is positive, the sum of τ*-ineff* lags is negative and all coefficient estimates are statistically significant at the 10% confidence level (or less). The lagged coefficients of E/A and control variables (with the exception of IR and GDPP) do not display a statically significant relationship with τ*-ineff* at the 10%

[18] Estimated correlations coefficients are available on request from the authors

confidence level. These results support the view that, as banks take-on more credit risks, they increase interest income so enhancing revenue efficiency (or reducing its revenue inefficiency), as predicted by the "luck" hypothesis.

The "bad management" and "luck" hypotheses may appear to contrast with one another since a NPL/L increase temporally precede a cost efficiency decline and a revenue inefficiency enhancement (i.e. *x-ineff* increase and *τ-ineff* decline). However, these results are consistent with the view that changes in bank risk-taking produce different effects on bank costs and revenues: for instance, greater credit risk-taking involves higher costs to better manage these risks and also higher interest revenues. Cost and revenue efficiency effects have also counterbalancing effects on bank's ability to internally generate equity capital: this seems to be consistent with the estimation of non-statistically significant coefficients for the NPP/L, cost and revenue efficiency estimates in the model using E/A as the dependent variable ($y=E/A$). Here few regression coefficients are found to be statistically significant: e.g. the $\tau\text{-}ineff_{t-1}$, NPL/L_{t-1} , and NPL/L_{t-1}. These results are consistent with the view that the: 1) equity capital ratio is influenced by short-term changes in bank efficiency and risk; 2) revenue efficiency changes precede (by one year) equity capital changes: namely, a revenue efficiency decrease is followed by a capital decline; and finally 3) greater risk-taking at time t-1 and t-2 precede capital reductions at time t.

When we use NPL/L as the dependent variable (i.e. $y=NPL/L$), the sum of all lagged cost inefficiency coefficients is negative, the sum of revenue inefficiency lags is positive and the sum of NPL/L lags is positive: all sum estimates are statistically significant at the 1% confidence level. The lagged coefficients of E/A are not found to be statistically significant at the 10% or less and few control variables (i.e. concentration, interest rate and bank specialisation) are found to have a statistically significant influence on NPL/L.

These results show that: 1) as banks become more cost efficient, this increase NPL/L (probably banks reduce the amount of resources allocated to underwriting and monitoring loans resulting cost efficient in the short term and increasing NPLL in the medium term), as predicted by the "cost skimping" hypothesis; 2) as banks become more revenue inefficient, this increase NPL/L (probably revenue efficient banks have lower quality portfolios so these have higher interest rate in the short term and suffer higher credit losses in the medium-long term), as predicted by the "revenue skimping" hypothesis.

6.2. Results: Default risk (EDF and PD)

Tables 4 and 5 report the results from model (1) using four lags on capital, equity and risk variables where bank risk-taking is measured focusing on default risk by using both EDF and PD_{5Y}.

<<INSERT TABLE 4 HERE>>

<<INSERT TABLE 5 HERE>>

By measuring bank default risk within one year (EDF) and five years (PD_{5Y}), we consider two extreme risk measures. In both cost efficiency models (i.e. *y=x-ineff* in tables 4 and 5), the sum of all lagged risk coefficients are not statistically significant at the 10% level or less, but two lag terms (i.e. EDF_{t-3} and $PD_{5Y,\, t-1}$) are positive and statistically significant. While these results do not fully support the "bad management" hypotheses, they are somewhat consistent with the view that an increase in default risk temporally precedes an *x-ineff* increase. In both revenue efficiency models (i.e. *y=τ-ineff* in tables 4 and 5), the sum of all lagged risk coefficients is negative and statistically significant at the 10% or less: these support the "luck" hypotheses being consistent with the view that an increase in default risk temporally precedes interest revenue growth and, consequently a *τ-ineff* reduction. A common result in all *x-ineff* for all risk measures (NPL/L, EDF and PD_{5Y}) is the negative Granger causation between *τ-ineff* and *x-ineff*, (i.e. a revenue efficiency increase temporarily precedes a cost efficiency decrease) and this is strongly consistently with the "bad management" and "luck" hypotheses: for instance, a risk increase generates higher interest income (so increasing revenue efficiency) and this increases costs associated with managing lower quality loans (so reducing cost efficiency).

When we use EDF and PD_{5Y} as dependant variables, our results substantially changes. While we find that E/A, cost and revenue efficiencies are statistically significant predictors of EDF, *x-ineff* and E/A are found to negatively Granger-cause the bank PD_{5Y} (statistically significant at 10% or less). These results display that: a) cost efficiency increases temporally precede PD_{5Y} increases, as predicted by the "cost skimping" hypothesis; b) an equity capital reduction temporarily precedes a PD increase, as predicted by the moral hazard hypotheses.

6.2. Robustness checks

In order to further confirm the aforementioned findings, we conducted a number of robustness checks. Firstly, we estimate model (1) using the OLS methods, as done by Berger and DeYoung (1997) and Williams (2004). Our results (table 6) shows most of models run suffer from heteroskedasticity problems so we computed White-Huber-Eicker standard errors. Results are consistent with our previous discussion. In the X-EFF model (i.e. *y=x-ineff*), the sum of lagged NPL/L coefficients is positive and the sum of *τ-ineff* lags are negative and both coefficients are statistically significant at the 1% confidence level supporting the "bad management" hypothesis (i.e. as bank risks increase, x-efficiency decline). In the revenue efficiency model ($y=\tau$-*ineff*), the sum of all lagged EDF coefficients are negative and statistically at the 10% confidence level, supporting the "luck" hypothesis (i.e. as banks take on more credit risks they also increases interest income so enhancing revenue efficiency). In the NPL/L model (i.e. $y=NPL/L$), the sum of revenue inefficiency lags are positive and statistically significant at the 1% level supporting the "revenue skimping" hypothesis (as revenue efficiency decreases, NPL/L increases).

<<INSERT TABLE 6 >>

Secondly, we estimate the model using the Arellano-Bond (1991) model, which assumes a set of strict restrictions for the model to be valid: serial correlation in the first order errors and no second-order GMM residual serial correlation. These are shown in Table 7 are here few variables are found to be significant. This may be because when the data series are highly persistent the lagged levels may be weak instruments for first differences, see e.g. Bond, 2002[19].

<<INSERT HERE TABLE 7 >>

As such, thirdly, we estimate model (3) using the Blundell and Bond (1998) model, buy positing a AR(3) lag structure for bank risk, capital and efficiency. This change has substantial effects on our sample composition by increasing the number of observations, but also reduces the time period investigated. Despite the different sample composition, our results (table 8) confirm the "bad management" hypothesis (as NPL/L increase, x-efficiency decline) and the

[19] The Blundell and Bond (1998) model used in the paper employ a system GMM (SYS-GMM) estimator that was designed to overcome some of the limitations of the DIF-GMM.

“cost skimping” hypothesis (i.e. the sum of all lagged cost inefficiency coefficients is negative showing that as banks become more cost efficient, this increase NPL/L and PD_{5Y}).

<<INSERT TABLE 8 HERE>>

7. Conclusions

Our paper assesses the inter-temporal relationships among bank efficiency, capital and bank risk taking[20] in the EU-26 commercial banking industry between 1995 and 2007 by using Granger-causality methods (Berger and De Young 1997, Williams 2004) and advances the established literature by introducing revenue and profit efficiencies as well as ‘new’ default probability risk measures. In general, our results support the “bad management” hypothesis (i.e. poor cost efficiency temporarily precedes increased risk-taking, e.g. presumably due to inadequate loan underwriting, monitoring, and control by bank managers). We also find evidence of the “luck” hypothesis - as banks take on more credit risks they also boost their revenue efficiency. The “cost skimping” hypothesis is also supported in the credit risk model because as banks become more cost efficient this increases NPL/L. Finally, the “revenue skimping” hypothesis is also supported: the sum of revenue inefficiency lags is positive and the sum of NPL/L lags is positive showing that as banks become more revenue inefficient, this increase NPL/L. So there is a lot going on!

We extend our analysis by also including two default risk measures: within one year Expected Default Frequency (EDF) and the 5-year cumulative probability of default (PD_{5Y}). Using these risk measures we find some evidence that an increase in default risk temporally precedes a cost inefficiency

[20] See reviews by Berger, Herring and Szego (1995) and Jackson (1999).

increase. We also find that an increase in default risk temporally precedes interest revenue improvements. A common result is also that revenue efficiency increases temporarily precede cost efficiency declines and this is consistent with the “bad management” and “luck” hypotheses. Or to put another way, a risk increase generates higher interest income (so increasing revenue efficiency) and this increases costs associated with managing lower quality loans (so reducing cost efficiency). We also find that equity capital strength (E/A), cost and revenue inefficiencies are significant predictors of EDF, while cost inefficiencies and E/A negatively influence bank PD_{5Y}. These latter results suggest evidence of “cost skimping” and moral hazard issues. Overall we believe our results to be particularly interesting and novel, especially in the light of the credit turmoil from 2007. By considering detailed risk measures and cost, revenue and profit efficiency estimates, we find that higher performance (as reflected in greater efficiency) has not necessarily been related to higher managerial skills, rather to cost and revenue skimping and bad management.

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Table 1 – Variables used to investigate the relationship between bank risk, capital and efficiency

Variables	Symbol	Description
Cost inefficiency	x-ineff	x-eff are estimated using Stochastic Frontier analysis(*).
Revenue Inefficiency	τ-ineff	τ-eff are estimated using Stochastic Frontier analysis(*).
Profit Inefficiency	π-ineff	π-eff are estimated using Stochastic Frontier analysis(*).
Total Assets	TA	TA is the total value of bank assets(1)
Non Performing Loan ratio	NPL/L	NPL/L is the ratio of Euro value of non-performing loans over the total gross value of bank loans(1)
Expected Default Frequency™	EDF	EDF is the probability that a company will default within a year (2)
5-years Probability of Default	PD_{5Y}	PD_5Y is the cumulative probability that a company will default within 5 years (3)
Equity Capital Ratio	E/TA	E/TA is the Euro value of total equity divided by the Euro value of total assets (1)
Bank Specialisation	BS	BS, is the ratio between the Euro value of total loans and the Euro value of total assets(1)
Income Diversification	ID	ID is the net non-interest income to net operating income ratio (1)
Bank Asset Size	BAS	BAS is the Euro value of its total assets(1)
Domestic banking industry concentration	CONC	CONC is measured by the Herfindahl-Hirschman Index, i.e. the sum of the squares of the market shares of each individual firm(4).
Number of Financial Intermediaries	NCI	NCI is the number of credit institutions (5)
Interest Rate	IR	IR is the money market interest rate(6).
GDP Pro-capita	GDPP	Domestic GDP (in Euro) and number of inhabitants(6).
Population Density	POPD	Number of habitants per Km^2 (6).

* More detail for the estimation procedures are provided in the Annex.

(1) Source of data: Bankscope
(2) Source of data: KMV-Moody's
(3) Source of data: Moody's ratings and PD estimates
(4) Source of data: ECB, EU Banking Structures, reports
(5) Source of data: ECB, MFI statistical reports
(6) Source of data: United Nation (UN) data

Table 2 – Descriptive statistics of variables used to analyse the sample of EU-26 area banks over the period 1995-2007

Variable	Observation	Mean	Standard Deviation	Min	Max
TA(*)	2232	58	191	0.0001	249000
x-ineff	2248	0.3733	0.2574	0.0008	1.0000
τ*-ineff*	2248	0.4569	0.2868	0.0000	1.0000
π*-ineff*	2248	0.5901	0.2842	0.0000	1.0000
PD_{5Y}	1987	0.0082	0.0198	0.0020	0.2509
EDF	2236	0.0050	0.0035	0.0000	0.0306
NPL/L	2248	0.0342	0.0134	0.0097	0.1167
E/TA	2244	0.5154	0.2500	0.1112	0.9975
CONC	2248	0.0852	0.0658	0.0081	0.4100
NCI	2248	621.1063	659.0082	7.0000	2968
ID	2248	0.2013	0.1341	-0.1300	0.9200
IR	2248	0.7759	0.3487	0.0000	3.5200
IR	2248	0.0784	0.0273	0.0000	0.2300
GDPG	2248	0.0249	0.0228	-0.0400	0.1300
GDPP	2248	10.0660	0.3041	8.7749	10.6436
POD	2247	4.0750	1.1922	1.2165	7.1500

(*) Data are in Euro million

Table 3 – Granger causality test for the relationship among banking capital, efficiency and credit risk (measured by NPL/L)

	Y=x-ineff$_t$		Y=τ-ineff$_t$		Y=E/TA$_t$		Y=NPL/L$_t$	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Intercept	-1.6984**	0.6733	1.9682	1.2328	1.8719	3.1564	-0.0228	0.0707
x-ineff$_{t-1}$	0.1765**	0.0792	0.1048	0.1328	0.8024*	0.4515	-0.0215**	0.0107
x-ineff$_{t-2}$	-0.0725	0.0577	0.0697	0.1227	0.3636	0.3173	-0.0068	0.0079
x-ineff$_{t-3}$	-0.1156	0.0887	0.3736**	0.1540	-0.7498	0.5215	-0.0167**	0.0080
x-ineff$_{t-4}$	-0.0052	0.0852	-0.0845	0.1293	0.1171	0.2961	-0.0077	0.0080
x-ineff$_{total}$	0.1040	0.1160	0.5481***	0.1861	0.4162	0.5679	-0.0450***	0.0128
τ-ineff$_{t-1}$	-0.0650	0.1040	-0.0624	0.1384	-0.7964*	0.4341	0.0160*	0.0092
τ-ineff$_{t-2}$	-0.1042	0.0947	-0.3001**	0.1316	-0.7348	0.4986	0.0228***	0.0085
τ-ineff$_{t-3}$	-0.1095	0.1041	-0.4026***	0.1465	0.3616	0.3659	0.0106	0.0066
τ-ineff$_{t-4}$	0.0022	0.0711	-0.0334	0.1479	0.1308	0.3445	-0.0038	0.0077
τ-ineff$_{total}$	-0.2787*	0.1661	-0.3625*	0.2010	-1.1696	0.09187	0.04942***	0.0163
NPL/L$_{t-1}$	1.4817	1.5549	1.4504	2.5852	-16.2188**	7.5635	0.4146***	0.1366
NPL/L$_{t-2}$	1.5931	1.5203	-4.5590	2.8759	-15.6304**	7.4354	0.3258**	0.1532
NPL/L$_{t-3}$	0.6966	1.5000	-6.9271**	3.0810	10.9243	8.1616	0.1335	0.1326
NPL/L$_{t-4}$	2.1890*	1.1861	0.3188	2.6988	-0.9605	6.0909	-0.1365	0.1853
NPL/L$_{total}$	3.7714*	2.2946	-10.0357*	5.3464	-20.9248	13.0286	0.7404***	0.2126
E/TA$_{t-1}$	0.0211	0.0227	-0.0440	0.0424	0.2845***	0.1041	0.0002	0.0025
E/TA$_{t-2}$	-0.0255	0.0226	-0.0257	0.0393	0.0750	0.0837	-0.0019	0.0024
E/TA$_{t-3}$	-0.0110	0.0249	-0.0079	0.0369	0.0171	0.0794	0.0002	0.0022
E/TA$_{t-4}$	0.0211	0.0217	0.0229	0.0431	-0.0124	0.0878	-0.0035	0.0031
E/TA$_{total}$	-0.01541	0.0406	-0.07762	0.0686	0.3595**	0.1467	-0.0014	0.0032
Ln (TA)	-0.0079*	0.0041	-0.0010	0.0063	-0.0113	0.0152	0.0004	0.0003
CONC	-1.0627	0.6193	-1.4940	0.9655	1.5851	2.5689	0.0200	0.0656
Ln(NCI)	-0.0012	0.0345	-0.0229	0.0505	-0.1206	0.1769	0.0067*	0.0040
ID	0.0225	0.1411	-0.2197	0.1978	-0.5885	0.5276	-0.0032	0.0169
BS	-0.1939***	0.0521	0.1650**	0.0714	0.0885	0.2059	-0.0075*	0.0042
IR	1.6273***	0.5571	-0.0266	0.8202	-2.0262	2.5291	-0.0917*	0.0532
GDPG	-1.8420*	0.8935	1.0199	1.0271	-1.0384	2.8889	-0.0345	0.0614
Ln(GDPP)	0.0832	0.0711	-0.2027**	0.1018	-0.0893	0.3136	-0.0024	0.0067
Ln(POD)	0.0001	0.0100	0.0125	0.0147	0.0531	0.0428	-0.0004	0.0008
Sample period:	1995-2007		1995-2007		1995-2007		1995-2007	
Sample composition:	EU25 commercial banks		EU25 commercial banks		EU25 commercial banks		EU25 commercial banks	
Observations:	703		703		703		703	
Sargan test, 2nd step, $\chi^2(114)$	65.5586		62.8037		60.9105		63.8949	
AB test AR(1)	-2.9379***		-4.5092***		-3.0171***		-3.8949***	
AB test AR(2)	-1.5578		0.7014		0.0744		1.5385	

Note: We reported asymptotic standard errors. The symbols *, **, and *** represent significance levels of 10%, 5% and 1% respectively. The Sargan/Hensen test of over-identifying restrictions for the GMM estimators: the null hypothesis is that instruments used are not correlated with residuals and so the over-identifying restrictions are valid. Arellano-Bond (AB) test for serial correlation in the first-differenced residuals. The null hypothesis id that errors in the first difference regression exhibit no second order serial correlation.

Table 4 – Granger causality test for the relationship among banking capital, efficiency and default risk (measured by EDF)

	Y=x-ineff$_t$		Y=τ-ineff$_t$		Y=E/TA$_t$		Y=EDF$_t$	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Intercept	-1.4608**	0.7426	1.4203	0.8974	3.0840	2.9872	0.7515	0.6141
x-ineff$_{t-1}$	0.2727***	0.0601	0.2404**	0.1197	-0.0805	0.3548	0.0120	0.0798
x-ineff$_{t-2}$	-0.0496	0.0504	-0.1546	0.1229	0.4800*	0.2882	-0.1010	0.0725
x-ineff$_{t-3}$	-0.0478	0.0882	0.1311	0.1196	-0.5904	0.4039	-0.0003	0.0636
x-ineff$_{t-4}$	0.0092	0.0897	-0.1016	0.1173	0.2296	0.2498	0.1063	0.0840
x-ineff$_{total}$	0.2232***	0.0870	0.2169	0.1571	-0.1908	0.4514	-0.8931	0.1014
τ-ineff$_{t-1}$	-0.1022	0.0763	-0.0292	0.0777	-0.3645	0.2477	-0.0506	0.0683
τ-ineff$_{t-2}$	-0.1835***	0.0681	-0.0865	0.0693	0.0141	0.2179	-0.0229	0.0661
τ-ineff$_{t-3}$	-0.1294**	0.0647	-0.0572	0.0959	-0.1103	0.2314	0.0206	0.0661
τ-ineff$_{t-4}$	-0.0864	0.0659	0.0005	0.0985	0.0527	0.2219	-0.0272	0.0562
τ-ineff$_{total}$	-0.4151***	0.1367	-0.1158	0.1213	-0.4607	0.5235	-0.0528	0-1434
EDF$_{t-1}$	-0.0894	0.0980	0.1733	0.1440	-0.3382	0.4154	1.1065***	0.0601
EDF$_{t-2}$	-0.0766	0.1481	-0.1160	0.1837	0.0385	0.6156	-0.0146	0.1242
EDF$_{t-3}$	0.3109**	0.1257	-0.3331**	0.1683	-0.1160	0.6516	-0.2349	0.1820
EDF$_{t-4}$	-0.1338	0.1113	0.2856*	0.1692	0.4639	0.4615	0.1961	0.1249
EDF$_{total}$	0.1449	0.1047	-0.2757*	0.1561	-0.4158	0.4304	1.0919***	0.1088
E/TA$_{t-1}$	-0.0021	0.0243	0.0215	0.0351	0.2700**	0.1085	0.0002	0.0275
E/TA$_{t-2}$	-0.0260	0.0212	-0.0486	0.0410	0.0449	0.0913	-0.0101	0.0229
E/TA$_{t-3}$	-0.0182	0.0222	0.0469	0.0352	0.0046	0.0962	0.0413*	0.0213
E/TA$_{t-4}$	0.0111	0.0256	-0.0330	0.0340	-0.0522	0.0888	0.0042	0.0186
E/TA$_{total}$	-0.0463	0.0413	0.0198	0.0485	0.3150**	0.1563	0.0314	0.0356
Ln (TA)	-0.0056	0.0038	-0.0049	0.0055	-0.0011	0.0133	-0.0007	0.0033
CONC	-0.9489	0.7827	-0.1398	0.7159	-0.4089	2.4168	-0.2716	0.6242
Ln(NCI)	-0.0149	0.0346	0.0239	0.0456	0.0021	0.1329	-0.0318	0.0341
ID	-0.0003	0.1393	-0.1385	0.1863	-0.5428	0.4927	0.0598	0.0869
BS	-0.1862***	0.0486	0.2336***	0.0763	0.1019	0.1788	-0.0064	0.0382
IR	1.4598**	0.5749	0.3258	0.7128	-0.7767	2.2630	1.3971**	0.5623
GDPG	-2.1494**	0.8543	0.4871	1.0225	1.8177	2.3884	0.0901	0.7657
GDPP	0.0953	0.0735	-0.2250**	0.0900	-0.3623	0.3058	-0.0339	0.0540
POD	-0.0054	0.0103	0.0215	0.0142	0.0522	0.0342	-0.0047	0.0071
Sample period:	1995-2007		1995-2007		1995-2007		1995-2007	
Sample composition:	EU25 commercial banks		EU25 commercial banks		EU25 commercial banks		EU25 commercial banks	
Observations:	703		703		703		703	
Sargan test, 2nd step, $\chi^2(114)$	131.2573		130.0867		121.4779		55.5239	
AB test AR(1)	-3.1801***		-6.0348***		-3.0523***		-6.2121***	
AB test AR(2)	-1.1677		1.5743		0.2948		-1.1676	

Note: We reported asymptotic standard errors. The symbols *, **, and *** represent significance levels of 10%, 5% and 1% respectively. The Sargan/Hensen test of over-identifying restrictions for the GMM estimators: the null hypothesis is that instruments used are not correlated with residuals and so the over-identifying restrictions are valid. Arellano-Bond (AB) test for serial correlation in the first-differenced residuals. The null hypothesis id that errors in the first difference regression exhibit no second order serial correlation.

Table 5 – Granger causality test for the relationship among banking capital, efficiency and default risk (measured by PD_{5Y})

	$Y=x\text{-ineff}_t$		$Y=\tau\text{-ineff}_t$		$Y=E/TA_t$		$Y=PD_{5Y}$	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Intercept	-2.5674***	0.7996	2.2207*	1.1527	-0.4672	2.9769	0.2381	0.1872
$x\text{-ineff}_{t-1}$	0.1353*	0.0697	0.1218	0.1205	0.3214	0.4208	-0.0419*	0.0248
$x\text{-ineff}_{t-2}$	-0.0878	0.0612	-0.0864	0.1435	0.4859	0.3263	-0.0134	0.0189
$x\text{-ineff}_{t-3}$	-0.0568	0.0796	0.2703*	0.1423	-0.4344	0.4751	-0.0098	0.0243
$x\text{-ineff}_{t-4}$	-0.0149	0.0784	-0.1874	0.1342	0.3375	0.2948	0.0279	0.0197
$x\text{-ineff}_{total}$	0.0475	0.1085	0.3057	0.2002	0.3729	0.5494	-0.0651***	0.0253
$\tau\text{-ineff}_{t-1}$	-0.1682*	0.0867	-0.0331	0.0899	-0.1984	0.3131	-0.0063	0.0147
$\tau\text{-ineff}_{t-2}$	-0.2218***	0.0767	-0.1075	0.0769	-0.0020	0.2356	-0.0219*	0.0122
$\tau\text{-ineff}_{t-3}$	-0.0580	0.0593	-0.0727	0.1061	0.0436	0.2922	-0.0051	0.0180
$\tau\text{-ineff}_{t-4}$	-0.0495	0.0676	-0.0671	0.1075	0.2320	0.2217	0.0020	0.0128
$\tau\text{-ineff}_{total}$	-0.4480***	0.1673	-0.1406	0.1431	-0.1568	0.6131	-0.0333	0.02594
$PD_{5Y,\ t-1}$	0.7137*	0.4277	0.3422	0.6266	0.5073	1.7314	1.2974***	0.1050
$PD_{5Y,\ t-2}$	-0.3503	0.5536	0.4356	0.7291	-2.1134	2.2483	-0.2183**	0.1086
$PD_{5Y,\ t-3}$	-0.4703	0.6204	-2.1995**	1.0192	4.3117	3.1949	-0.2030	0.1648
$PD_{5Y,\ t-4}$	0.0766	0.4669	1.5347*	0.8307	-2.8736	2.1827	0.1447	0.1311
$PD_{5Y,\ total}$	-0.1070	0.4567	-1.4218*	0.7788	2.7057	2.1364	1.0791***	0.0857
E/TA_{t-1}	0.0295	0.0245	-0.0300	0.0408	0.3960***	0.0796	-0.0085	0.0067
E/TA_{t-2}	-0.0099	0.0252	-0.0358	0.0361	0.0788	0.0815	-0.0103*	0.0060
E/TA_{t-3}	0.0004	0.0238	0.0241	0.0361	-0.0140	0.0957	0.0050	0.0070
E/TA_{t-4}	0.0031	0.0235	0.0006	0.0401	-0.0221	0.0817	0.0036	0.0061
E/TA_{total}	0.0200	0.0396	-0.0417	0.0484	0.4748***	0.1119	-0.1374*	0.0079
Ln (TA)	-0.0105**	0.0046	-0.0023	0.0059	0.0040	0.0122	0.0012*	0.0006
CONC	0.1135	0.9247	-1.9780*	1.0448	2.6312	3.1500	0.0766	0.1431
Ln(NCI)	0.0554	0.0509	-0.0278	0.0607	0.0079	0.2011	0.0005	0.0060
ID	0.0308	0.1447	-0.0687	0.1935	-1.0131	0.5478	0.0031	0.0261
BS	-0.2244***	0.0435	0.1976***	0.0732	0.0362	0.2098	-0.0060	0.0096
IR	1.1431*	0.5928	-0.0396	0.8622	-1.4965	2.2159	0.1342	0.1176
GDPG	-2.9027***	1.0288	0.5739	0.9221	0.7951	2.5380	-0.1158	0.1177
GDPP	0.1372*	0.0730	-0.1982***	0.0772	-0.0563	0.2818	-0.0215	0.0166
POD	-0.0057	0.0106	0.0057	0.0147	0.0782**	0.0355	0.0006	0.0020
Sample period:	1995-2007		1995-2007		1995-2007		1995-2007	
Sample composition:	EU25 commercial banks		EU25 commercial banks		EU25 commercial banks		EU25 commercial banks	
Observations:	659		659		659		659	
Sargan test, 2nd step, $\chi^2(114)$	133.5734		126.3366		88.0416		78.4128	
AB test AR(1)	-2.9921***		-5.3532***		-3.3822***		-5.3828***	
AB test AR(2)	-0.5199		1.0197		0.02339		0.1996	

Note: We reported asymptotic standard errors. The symbols *, **, and *** represent significance levels of 10%, 5% and 1% respectively. The Sargan/Hensen test of over-identifying restrictions for the GMM estimators: the null hypothesis is that instruments used are not correlated with residuals and so the over-identifying restrictions are valid. Arellano-Bond (AB) test for serial correlation in the first-differenced residuals. The null hypothesis id that errors in the first difference regression exhibit no second order serial correlation.

Table 6 – Robustness check: Granger causality test for the relationship among banking capital, efficiency and default risk estimated using OLS

	Models where Risk =NPL/L				Models where Risk =EDF				Models where Risk = PD_{5Y}			
	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=NPL/L	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=EDF	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=PD_{5Y}
Intercept	-1.2492***	0.1798	2.5539*	0.0149*	-1.0948***	0.0858	2.3451*	0.0828	-1.1286***	0.2471	2.6695**	0.0229
	(0.3444)	(0.3880)	(1.3821)	(0.0258)	(0.3282)	(0.3738)	(1.3517)	(0.2260)	0.3479	0.3991	1.4348	0.0616
x-$ineff_{t-1}$	0.4581***	-0.0594	-0.0352	0.0024	0.4701***	-0.0636	-0.0836	-0.0139	0.4726***	-0.0550	-0.0043	-0.0028
	(0.0671)	(0.0501)	(0.1670)	(0.0033)	(0.0671)	(0.0499)	(0.1714)	(0.0367)	0.0719	0.0519	0.1743	0.0082
x-$ineff_{t-2}$	0.0243	-0.0611	0.2375	0.0024	0.0271	-0.0641	0.2570	-0.0215	0.0285	-0.0717	0.2394	-0.0050
	(0.0447)	(0.0516)	(0.1744)	(0.0031)	(0.0444)	(0.0517)	(0.1789)	(0.0399)	0.0469	0.0544	0.1792	0.0084
x-$ineff_{t-3}$	0.0139	0.0676	0.0181	-0.0027	0.0093	0.0628	0.0364	-0.0036	0.0151	0.0916	-0.0568	0.0016
	(0.0408)	(0.0571)	(0.1882)	(0.0033)	(0.0415)	(0.0564)	(0.1886)	(0.0456)	0.0434	0.0593	0.2017	0.0095
x-$ineff_{t-4}$	0.0605	-0.0233	-0.0224	-0.0013	0.0490	-0.0160	-0.0399	0.0183	0.0542	-0.0508	-0.0656	0.0005
	(0.0425)	(0.0556)	(0.1654)	(0.0033)	(0.0426)	(0.0546)	(0.1636)	(0.0352)	0.0450	0.0552	0.1721	0.0088
x-$ineff_{total}$	0.5569***	-0.0763	0.1981	0.0007	0.5555***	-0.0809	0.1699	-0.0207	0.5704***	-0.0858	0.1127	-0.0057
	(0.0492)	(0.0511)	(0.1665)	(0.0037)	(0.0488)	(0.0510)	(0.1683)	(0.0352)	(0.0531)	(0.0537)	(0.1904)	0.0095
τ-$ineff_{t-1}$	0.0162	0.0713	-0.0949	0.0138***	-0.0064	0.0648*	0.0638	-0.0452*	-0.0048	0.0803**	0.0857	0.0029
	(0.0356)	(0.0440)	(0.1449)	(0.0047)	(0.0316)	(0.0391)	(0.1174)	(0.0259)	0.0316	0.0404	0.1224	0.0064
τ-$ineff_{t-2}$	-0.0228	-0.0020	-0.1672	0.0033	-0.0486*	0.0250	-0.1184	-0.0577**	-0.0480	0.0229	-0.1140	0.0005
	(0.0330)	(0.0514)	(0.1588)	(0.0041)	(0.0294)	(0.0431)	(0.1173)	(0.0259)	0.0303	0.0444	0.1252	0.0069
τ-$ineff_{t-3}$	0.0238	-0.0443	0.3040*	0.0082*	0.0023	-0.0544	0.0074	0.0515**	-0.0034	-0.0641	0.0311	0.0058
	(0.0338)	(0.0506)	(0.1700)	(0.0043)	(0.0286)	(0.0423)	(0.1065)	(0.0260)	0.0303	0.0445	0.1074	0.0062
τ-$ineff_{t-4}$	-0.0411	0.0269	-0.0290	-0.0009	-0.0382	0.0361	0.1304	0.0213	-0.0359	0.0229	0.1300	0.0018
	(0.0338)	(0.0462)	(0.1486)	(0.0050)	(0.0282)	(0.0401)	(0.1167)	(0.0250)	0.0306	0.0413	0.1202	0.0059
τ-$ineff_{total}$	-0.0239	0.0519	0.0129	0.0244***	-0.0909*	0.0714	0.0831	-0.0301	-0.0921***	0.0619	0.1328	0.0108
	(0.0550)	(0.0753)	(0.2570)	(0.0056)	(0.0489)	(0.0696)	(0.2271)	(0.0466)	(0.0493)	(0.0720)	(0.2394)	(0.106)
$Risk_{t-1}$	0.5926	0.0484	-4.1898	0.4391***	-0.0050	-0.0622	0.0217	1.1583***	0.1779	-0.1433	-0.8735	1.2852***
	(0.3967)	(0.5179)	(2.5569)	(0.1078)	(0.0390)	(0.0584)	(0.2187)	(0.0472)	0.2021	0.2580	0.8838	0.0497
$Risk_{t-2}$	0.7061	-0.5858	-0.7409	0.1612*	0.0003	0.1723**	0.0299	0.0909	-0.3738	0.5837	0.6435	-0.0544
	(0.4742)	(0.6708)	(2.8930)	(0.0875)	(0.0587)	(0.0851)	(0.3383)	(0.1057)	0.3574	0.4253	1.5818	0.0825
$Risk_{t-3}$	0.6043	0.2294	7.5784**	0.0488	0.0560	0.0174	-0.1808	-0.2140**	0.1051	-0.7283	-0.0466	-0.1735**
	(0.5084)	(0.6713)	(3.5617)	(0.0919)	(0.0614)	(0.0946)	(0.3433)	(0.1138)	0.3219	0.5271	1.3530	0.0869
$Risk_{t-4}$	-0.0885	-0.1087	-4.3372	0.1032	-0.0474	-0.1385**	0.1203	-0.0279	0.0925	0.2927	0.3258	-0.0540
	(0.4455)	(0.5594)	(2.7436)	(0.1014)	(0.0429)	(0.0658)	(0.2138)	(0.0504)	0.1866	0.3225	0.8718	0.0516
$Risk_{total}$	1.8145***	-0.4166	-1.6895	0.7522***	0.0039	-0.0110**	-0.0089	1.007***	0.0017	0.0048	0.0492	1.0033***
	(0.5081)	(0.7448)	(2.9931)	(0.1100)	0.0034	(0.0049)	(0.0142)	(0.0028)	(0.0065)	(0.0134)	(0.0327)	(0.0020)
E/TA_{t-1}	0.0158*	-0.0083	0.4270***	0.0020**	0.0137	-0.0088	0.4311***	0.0215**	0.0114	-0.0059	0.4526***	-0.0037*
	(0.0083)	(0.0123)	(0.0641)	(0.0008)	(0.0084)	(0.0122)	(0.0653)	(0.0106)	0.0089	0.0126	0.0658	0.0021
E/TA_{t-2}	-0.0133	-0.0083	0.1345**	-0.0002	-0.0121	-0.0080	0.1197*	-0.0163	-0.0091	-0.0119	0.1102	-0.0005
	(0.0101)	(0.0137)	(0.0704)	(0.0009)	(0.0102)	(0.0135)	(0.0718)	(0.0102)	0.0108	0.0142	0.0699	0.0023
E/TA_{t-3}	-0.0062	0.0079	0.0221	0.0015	-0.0046	0.0047	0.0236	-0.0040	-0.0046	0.0065	0.0269	0.0004
	(0.0102)	(0.0135)	(0.0590)	(0.0011)	(0.0103)	(0.0133)	(0.0600)	(0.0089)	0.0104	0.0137	0.0588	0.0024
E/TA_{t-4}	-0.0060	0.0281**	0.0164	-0.0044***	-0.0073	0.0263**	0.0196	0.0091	-0.0088	0.0332**	0.0114	0.0007
	(0.0101)	(0.0132)	(0.0530)	(0.0012)	(0.0103)	(0.0130)	(0.0536)	(0.0078)	0.0105	0.0133	0.0540	0.0021
E/TA_{total}	-0.0098	0.0194	0.5999***	-0.0011	-0.0103	0.0714	0.5939***	0.0103	-0.0111	0.0218*	0.6011***	-0.0032

	Models where Risk =NPL/L				Models where Risk =EDF				Models where Risk = PD_{5Y}			
	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=NPL/L	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=EDF	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=PD_{5Y}
	(0.0087)	(0.0125)	(0.0589)	(0.0010)	(0.0092)	(0.0696)	(0.0608)	(0.0084)	(0.0093)	(0.01296)	(0.0608)	(0.0021)
Ln (TA)	0.0007	-0.0059**	0.0015	-0.0001	0.0004	-0.0054*	0.0026	-0.0003	-0.0002	-0.0060**	0.0052	0.0002
	(0.0019)	(0.0029)	(0.0080)	(0.0002)	(0.0019)	(0.0028)	(0.0084)	(0.0018)	0.0019	0.0028	0.0079	0.0004
CONC	-0.4710***	0.3135**	0.0917	-0.0254***	-0.4899***	0.3130**	0.0974	-0.0532	-0.4712***	0.2777*	0.1967	-0.0162
	(0.1476)	(0.1472)	(0.4483)	(0.0095)	(0.1494)	(0.1446)	(0.4543)	(0.1108)	0.1606	0.1491	0.5027	0.0231
Ln(NCI)	0.0166**	0.0201**	-0.0079	-0.0003	0.0181	0.0206**	-0.0079	-0.0144**	0.0153*	0.0174*	0.0199	-0.0003
	(0.0080)	(0.0093)	(0.0305)	(0.0006)	(0.0081)	(0.0091)	(0.0306)	(0.0058)	0.0083	0.0097	0.0342	0.0016
ID	-0.1301***	-0.1083**	-0.1285	0.0032	-0.1319	-0.1118**	-0.1275	-0.0040	-0.1294***	-0.1028*	-0.0581	-0.0057
	(0.0478)	(0.0520)	(0.2130)	(0.0057)	(0.0473)	(0.0506)	(0.2221)	(0.0356)	0.0495	0.0532	0.2276	0.0095
BS	-0.0692***	0.0438**	0.0965	-0.0025*	-0.0744***	0.0451**	0.0927	0.0281**	-0.0739***	0.0430**	0.0944	-0.0044
	(0.0187)	(0.0177)	(0.0810)	(0.0013)	(0.0191)	(0.0176)	(0.0814)	(0.0132)	0.0199	0.0188	0.0893	0.0031
IR	1.4403***	0.3457	-0.5544	-0.0319	1.4276***	0.2998	-0.4356	0.3938	1.5312***	0.1689	-0.9726	0.0448
	(0.3455)	(0.4079)	(1.3951)	(0.0258)	(0.3414)	(0.4106)	(1.4041)	(0.2412)	0.3666	0.4274	1.4889	0.0612
GDPG	-0.5941	0.3187	1.2264	-0.0285	-0.6125	0.3774	1.1437	-0.5895	-0.7461	0.1511	2.1835	0.0743
	(0.4802)	(0.4390)	(1.2902)	(0.0246)	(0.4718)	(0.4292)	(1.2888)	(0.3872)	0.5222	0.4658	1.3641	0.0679
GDPP	0.0783**	-0.0824	-0.2663**	0.0017	0.0693**	-0.0807**	-0.2581**	-0.0021	0.0739**	-0.0844**	-0.2888**	-0.0003
	(0.0327)	(0.0362)	(0.1305)	(0.0024)	(0.0316)	(0.0352)	(0.1308)	(0.0215)	0.0339	0.0378	0.1379	0.0057
POD	-0.0172***	0.0193***	0.0138	-0.0008*	-0.0187***	0.0181***	0.0141	-0.0008	-0.0188***	0.0192***	0.0261	-0.0016
	(0.0049)	(0.0071)	(0.0195)	(0.0004)	(0.0049)	(0.0069)	(0.0196)	(0.0043)	0.0053	0.0072	0.0203	0.0010
Sample period:	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007
Sample composition:	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks
Observations:	703	703	703	703	703	703	703	703	659	659	659	659
R-square	0.7373	0.1002	0.3331	0.3763	0.7334	0.1151	0.3218	0.9944	0.7263	0.1042	0.3403	0.9988
F-test, F (25,677)	95.77***	3.89***	9.94***	7.09***	96.01***	4.38***	9.91***	6476.77***	86.91***	2.94***	9.73***	20611.89***
R-R test, p-value	0.0043	0.0786	0.0000	0.0003	0.0022	0.0254	0.0007	0.0016	0.0282	0.0355	0.0002	0.0000
White's test, p-value	0.0000	0.8547	0.0001	0.0000	0.0000	0.9534	0.0000	0.0000	0.0000	0.3799	0.0000	0.0222
BS/CW test,p-value	0.2619	0.0471	0.0000	0.0000	0.4845	0.0297	0.0000	0.0000	0.2816	0.0897	0.0000	0.9951

Note: We reported in brackets robust standard errors (i.e. the White-Huber-Eicker standard errors) to account for heteroskedasticity problems. The R-R test is the Ramsey Reset test and the null hypothesis is that the model has no omitted variables. The White's test null hypothesis is the homoskedasticity. The BS/CW test is the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity and the null hypothesis is the Constant variance. The symbols *, **, and *** represent significance levels of 10%, 5% and 1% respectively.

Table 7 – Robustness check: Granger causality test for the relationship among banking capital, efficiency and default risk estimated using Arellano and Bond (1991) model

	Models where Risk =NPL/L				Models where Risk =EDF				Models where Risk = PD_{5Y}			
	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=NPL/L	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=EDF	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=PD_{5Y}
Intercept	-0.8613	-0.2803	-1.5865	0.2308**	-1.0623	-1.7891	2.6177	-1.4755	1.3646	-1.7684	-3.7079	-2.1436***
	(1.2531)	(2.0688)	(4.8090)	(0.1041)	(1.1477)	(1.3885)	(3.5198)	(1.0875)	(1.8808)	(3.6011)	(6.8560)	(0.3405)
x-$ineff_{t-1}$	0.0111	0.0615	-0.1069	-0.0089	0.0006	0.2333*	0.0022	-0.0347	-0.1292	0.1639	-0.1492	0.0237
	(0.1018)	(0.1360)	(0.4448)	(0.0094)	(0.0942)	(0.1393)	(0.4069)	(0.0871)	(0.1027)	(0.1359)	(0.3416)	(0.0205)
x-$ineff_{t-2}$	-0.1447***	0.0060	0.0553	-0.0058	-0.1845***	0.0038	0.9089**	0.0186	-0.2095***	-0.0174	0.5827	0.0010
	(0.0528)	(0.1330)	(0.2967)	(0.0076)	(0.0523)	(0.1204)	(0.3871)	(0.0812)	(0.0606)	(0.1528)	(0.3843)	(0.0160)
x-$ineff_{t-3}$	-0.2152**	0.3927***	-0.7088**	-0.0198**	-0.1804**	0.2000*	0.0137	-0.0358	-0.2086***	0.3161**	-0.0724	-0.0069
	(0.0853)	(0.1452)	(0.3342)	(0.0080)	(0.0783)	(0.1178)	(0.3019)	(0.0738)	(0.0785)	(0.1263)	(0.3023)	(0.0177)
x-$ineff_{t-4}$	-0.1583	-0.0164	0.3094	-0.0118	-0.1506	0.0365	0.7615**	0.0170	-0.1465	-0.1177	0.6528**	0.0141
	(0.0998)	(0.1581)	(0.3598)	(0.0093)	(0.0954)	(0.1424)	(0.3360)	(0.0906)	(0.0992)	(0.1532)	(0.2969)	(0.0183)
x-$ineff_{total}$												
τ-$ineff_{t-1}$	-0.0265	-0.0484	-0.7930**	0.0070	-0.0684	-0.2282**	-0.6600**	-0.0349	-0.1183*	-0.2040**	-0.5918**	0.0061
	(0.0911)	(0.1732)	(0.4020)	(0.0089)	(0.0606)	(0.0912)	(0.2680)	(0.0644)	(0.0691)	(0.0967)	(0.3023)	(0.0140)
τ-$ineff_{t-2}$	-0.1308	-0.2342*	-0.4242	0.0122*	-0.1969***	-0.1798***	-0.1956	-0.0732	-0.2071***	-0.1771**	-0.4422**	-0.0268**
	(0.0847)	(0.1359)	(0.3672)	(0.0074)	(0.0590)	(0.0612)	(0.2481)	(0.0592)	(0.0649)	(0.0762)	(0.1877)	(0.0121)
τ-$ineff_{t-3}$	-0.2721***	-0.3548**	0.7265**	0.0032	-0.1443**	-0.1577	-0.2983	0.0137	-0.1391**	-0.1054	-0.3120	-0.0158
	(0.0983)	(0.1589)	(0.3663)	(0.0063)	(0.0617)	(0.1023)	(0.2073)	(0.0586)	(0.0660)	(0.1195)	(0.2285)	(0.0142)
τ-$ineff_{t-4}$	-0.0134	-0.0608	0.2907	-0.0054	-0.0777	-0.1762	-0.0845	-0.0948*	-0.0982	-0.1408	-0.0353	0.0090
	(0.0750)	(0.1633)	(0.3657)	(0.0077)	(0.0598)	(0.1166)	(0.2134)	(0.0575)	(0.0623)	(0.1153)	(0.2404)	(0.0172)
τ-$ineff_{total}$												
$Risk_{t-1}$	1.4857	4.4355	-13.0346	-0.1520	-0.0759	0.0089	-0.6377	0.6190***	1.3629***	0.5092	3.0926	0.5530***
	(1.8042)	(3.3651)	8.3254)	(0.1566)	(0.1140)	(0.1852)	(0.4791)	(0.1018)	(0.5212)	(0.6957)	(2.3341)	(0.1260)
$Risk_{t-2}$	-0.9548	-1.8440	-4.2695	-0.0290	-0.0791	-0.0582	-0.3377	0.0668	-0.3493	-0.1308	-3.4538	0.2181**
	(1.7830)	(3.4999)	7.7706)	(0.1215)	(0.1307)	(0.1844)	(0.4947)	(0.0955)	(0.4748)	(0.7846)	(2.1351)	(0.0904)
$Risk_{t-3}$	-2.9735	-5.2039	27.9145***	-0.1531	0.1733	0.2280	0.0879	-0.0997	-0.5745	-2.4640**	1.9949	-0.1104
	(1.8228)	(3.6236)	8.5938)	(0.1334)	(0.1153)	(0.1594)	(0.5465)	(0.1334)	(0.6530)	(1.0452)	(2.2319)	(0.1317)
$Risk_{t-4}$	3.0328*	0.7698	7.7127	-0.2305	0.0076	-0.3670*	0.4160	0.2165**	0.3460	1.9517**	-2.1254	-0.0466
	(1.5869)	(2.9922)	8.1900)	(0.1743)	(0.1099)	(0.2213)	(0.3293)	(0.1150)	(0.5721)	(0.8925)	(1.9838)	(0.1203)
$Risk_{total}$												
E/TA_{t-1}	-0.0346	-0.0885*	-0.0422	0.0035*	-0.0247	-0.0623	0.0050	0.0273	-0.0294	-0.0766*	0.1248	-0.0055
	(0.0291)	(0.0513)	(0.1235)	(0.0021)	(0.0322)	(0.0447)	(0.1354)	(0.0380)	(0.0326)	(0.0410)	(0.1415)	(0.0066)
E/TA_{t-2}	-0.0216	-0.0649	-0.0120	0.0022	-0.0131	-0.0900**	-0.0168	0.0484**	-0.0192	-0.0788**	-0.0329	-0.0026
	(0.0256)	(0.0454)	(0.0874)	(0.0019)	(0.0280)	(0.0375)	(0.0858)	(0.0217)	(0.0272)	(0.0354)	(0.0771)	(0.0058)
E/TA_{t-3}	0.0232	-0.0353	-0.1123	0.0025	0.0290	-0.0143	-0.1131	0.0144	0.0297	-0.0371	-0.2124	0.0042
	(0.0246)	(0.0453)	(0.1434)	(0.0023)	(0.0243)	(0.0358)	(0.1421)	(0.0213)	(0.0253)	(0.0399)	(0.1673)	(0.0056)
E/TA_{t-4}	0.0669***	0.0189	-0.0456	-0.0036	0.0584***	-0.0072	-0.0471	0.0232	0.0487**	0.0167	-0.0646	0.0120*
	(0.0244)	(0.0371)	(0.0899)	(0.0026)	(0.0208)	(0.0340)	(0.1073)	(0.0205)	(0.0230)	(0.0402)	(0.0948)	(0.0063)
E/TA_{total}												
Ln (TA)	-0.0073*	0.0013	-0.0279*	0.0000	-0.0073**	-0.0071	-0.0072	-0.0036	-0.0082**	-0.0044	-0.0055	0.0001
	(0.0041)	(0.0064)	(0.0159)	(0.0003)	(0.0037)	(0.0065)	(0.0105)	(0.0036)	(0.0042)	(0.0060)	(0.0132)	(0.0006)

	Models where Risk =NPL/L				Models where Risk =EDF				Models where Risk = PD_{5Y}			
	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=NPL/L	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=EDF	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=PD_{5Y}
CONC	-2.8720**	0.1833	1.5194	-0.1589*	-2.2223*	-0.1126	-0.6236	-0.1580	-1.1718	0.3907	6.2853*	0.1047
	(1.2398)	(1.2493)	(3.2114)	(0.0830)	(1.3368)	(1.1707)	(2.9227)	(0.9151)	(1.3547)	(1.2817)	(3.3495)	(0.1841)
Ln(NCI)	0.0838	0.1745	-0.0220	-0.0177**	0.1197	0.2314**	-0.4266	0.1662*	0.1419	0.2638***	-0.0444	0.0456**
	(0.1165)	(0.1381)	(0.3406)	(0.0077)	(0.1223)	(0.1088)	(0.2770)	(0.0912)	(0.1154)	(0.0969)	(0.2515)	(0.0183)
ID	-0.0437	-0.0459	-0.1608	-0.0079	0.0421	0.0053	-1.0456*	-0.0269	0.0118	0.1638	-0.8008	-0.0022
	(0.1508)	(0.2200)	(0.5413)	(0.0165)	(0.1393)	(0.1875)	(0.6097)	(0.0869)	(0.1431)	(0.1913)	(0.5837)	(0.0215)
BS	-0.1977***	0.1736**	0.2111	-0.0135***	-0.1878***	0.2139***	0.0557	-0.0412	-0.1869***	0.2512***	0.0293	-0.0127
	(0.0422)	(0.0781)	(0.1638)	(0.0045)	(0.0388v	(0.0736)	(0.1631)	(0.0378)	(0.0415)	(0.0787)	(0.1793)	(0.0096)
IR	0.3006	0.5052	1.9243	-0.1336***	0.2938	0.3045	-0.5891	0.6114	0.1655	0.5504	-0.6127	-0.1086
	(0.5765)	(0.8663)	(2.0220)	(0.0495)	(0.5131)	(0.7489)	(2.2443)	(0.4457)	(0.5600)	(0.7903)	(2.1013)	(0.1094)
GDPG	-1.3668	1.0037	0.0425	-0.0441	-1.7486***	0.7086	0.2288	-0.1808	-2.3899**	-0.1536	-2.3707	-0.2518**
	(1.0021)	(1.0898)	(2.3617)	(0.0572)	(1.0027)	(0.9590)	(2.2652)	(0.6449)	(0.9615)	(1.0829)	(2.7523)	(0.1004)
GDPP	-0.0572	-0.1477	-0.0340	-0.0068	-0.0497	-0.1278	-0.2656	-0.0624	0.0640	-0.1274	0.0412	-0.0090
	(0.0849)	(0.1363)	(0.3433)	(0.0075)	(0.0813)	(0.0952)	(0.2875)	(0.0603)	(0.0869)	(0.1201)	(0.3196)	(0.0160)
POD	0.0151	0.0048	0.0251	0.0009	0.0143	-0.0015	0.0116	-0.0013	0.0102	-0.0131	0.0339	-0.0008
	(0.0103)	(0.0151)	(0.0465)	(0.0007)	(0.0110)	(0.0145)	(0.0374)	(0.0072)	(0.0110)	(0.0168)	(0.0325)	(0.0018)
Sample period:	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007
Sample composition:	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks
Observations:	703	703	703	703	703	703	703	703	659	659	659	659
Sargan test, 2nd step, $\chi^2(114)$												
AB test AR(1)												
AB test AR(2)												

Note: We reported asymptotic standard errors in brackets. The symbols *, **, and *** represent significance levels of 10%, 5% and 1% respectively. The Sargan/Hensen test of over-identifying restrictions for the GMM estimators: the null hypothesis is that instruments used are not correlated with residuals and so the over-identifying restrictions are valid. Arellano-Bond (AB) test for serial correlation in the first-differenced residuals. The null hypothesis id that errors in the first difference regression exhibit no second order serial correlation.

Table 8 – Robustness check: Granger causality test for the relationship among banking capital, efficiency and default risk [with an AR(3) process] estimated using the Blundell and Bond (1998) method

	Models where Risk =NPL/L				Models where Risk =EDF				Models where Risk = PD_{5Y}			
	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=NPL/L	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=EDF	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=PD_{5Y}
Intercept	-0.9153	0.9897	0.3924	0.0297	-0.7461	0.7094	1.8341	0.5517	-0.9288	0.5989	-0.5174	0.0630
	(0.6043C	(0.7285)	(2.1555)	(0.0646)	(0.6289)	(0.6416)	(2.2157)	(0.4226)	(0.6284)	(0.7100)	(2.2314)	(0.1188)
x-$ineff_{t-1}$	0.2841***	0.1639	0.0554	-0.0194**	0.2898***	0.2180**	-0.2919	-0.0161	0.2551***	0.1540	-0.1584	-0.0301**
	(0.0613)	(0.0999)	(0.3298)	(0.0092)	(0.0611)	(0.1036)	(0.3038)	(0.0787)	(0.0588)	(0.1075)	(0.3053)	(0.0147)
x-$ineff_{t-2}$	-0.0071	-0.0428	0.0504	0.0025	-0.0161	-0.0455	0.3812	-0.0055	-0.0345	-0.0860	0.4222	-0.0141
	(0.0525)	(0.1109)	(0.2579)	(0.0068)	(0.0472)	(0.0993)	(0.2468)	(0.0719)	(0.0487)	(0.1176)	(0.3035)	(0.0162)
x-$ineff_{t-3}$	-0.0261	0.1418	-0.3443	-0.0066	-0.0428	0.0860	-0.4674*	-0.0290	-0.0052	0.1105	-0.3430	-0.0167
	(0.0671)	(0.1041)	(0.2775)	(0.0070)	(0.0646)	(0.0938)	(0.2807)	(0.0522)	(0.0672)	(0.0970)	(0.3298)	(0.0144)
x-$ineff_{total}$	0.2508**	0.2629*	-0.2384	-0.0234**	0.2309**	0.2585*	-0.3781	-0.0505	0.2154**	0.1786	-0.0792	-0.0609***
	(0.1127)-	(0.1367)	(0.3986)	(0.0109)	(0.1089)	(0.1369)	(0.3599)	(0.0880)	(0.1040)	(0.1430)	(0.3535)	(0.0197)
τ-$ineff_{t-1}$	-0.0763	-0.0149	-0.1564	0.0204**	-0.0881	0.0348	-0.2638	-0.0806	-0.1162*	0.0148	-0.1649	-0.0021
	(0.0737)	(0.0678)	(0.3340)	(0.0082)	(0.0668)	(0.0602)	(0.2479)	(0.0493)	(0.0650)	(0.0585)	(0.3018)	(0.0107)
τ-$ineff_{t-2}$	-0.1024	-0.2146**	-0.0624	0.0136*	-0.1764***	-0.0666	0.2491	-0.0624	-0.1543***	-0.0935	0.1774	-0.0200*
	(0.0799)	(0.0923)	(0.2811)	(0.0075)	(0.0640)	(0.0551)	(0.2518)	(0.0646)	(0.0524)	(0.0606)	(0.2638)	(0.0119)
τ-$ineff_{t-3}$	-0.0696	-0.1177	0.4238	-0.0025	-0.1232**	-0.0162	0.1837	0.0458	-0.1111*	-0.0742	0.2773	-0.0099
	(0.0866)	(0.1144)	(0.3241)	(0.0069)	(0.0596)	(0.0927)	(0.2421)	(0.0531)	(0.0601)	(0.0942)	(0.2410)	(0.0140)
τ-ineff $_{\lambda\alpha\tau o\tau}$	-0.2483**	-0.3472*	0.2050	0.0314**	-0.2877***		0.1690	-0.0972	-0.3816***	-0.1529	0.2898	-0.0319
	(0.1237)	(0.1654)	(0.6516)	(0.0134)	(0.1160)		(0.5095)	(0.0958)	(0.1072	(0.1753)	(0.5924)	(0.0213)
$Risk_{t-1}$	1.0770	0.8098	-1.4002	0.4644***	-0.0158	-0.0451	-0.5988*	1.1004***	0.3737	0.2889	1.6112	1.2528***
	(0.9638)	(1.3453)	(5.3120)	(0.1537)	(0.0837)	(0.1446)	(0.3314)	(0.0695)	(0.3998)	(0.4622)	(1.4440)	(0.0828)
$Risk_{t-2}$	-0.2471	-2.1778	-3.3706	0.1335	0.0443	0.0735	0.4662	-0.0298	-0.5051	0.3619	-1.7356	-0.2471**
	(1.1090)	(1.8846)	(6.0889)	(0.1126)	(0.1309)	(0.1709)	(0.4814)	(0.1276)	(0.5047)	(0.7303)	(1.9263)	(0.1081)
$Risk_{t-3}$	1.5425*	-0.7886	7.5049	-0.1517	-0.0194	-0.0334	0.1676	-0.0223	0.1544	-0.6601	-0.0314	0.0171
	(0.8647)	(2.0401)	(6.2356)	(0.1263)	(0.1278)	(0.1400)	(0.3958)	(0.1158)	(0.3475)	(0.5082)	(1.2525)	(0.0931)
$Risk_{total}$	2.3724*	-2.1566	2.7342	0.4461*	0.0091	-0.0050	0.03499	1.0482***	0.0229	-0.0093	-0.1558	1.0227***
	(1.4142)	(3.1247)	(9.2347)	(0.2179)	(0.0189)	(0.2109)	(0.0558)	(0.0191)	(0.0243)	(0.0348)	(0.1296)	(0.0099)
E/TA_{t-1}	0.0410**	-0.0326	0.2814***	0.0016	0.0233	-0.0283	0.3630***	0.0254	0.0173	-0.0283	0.3803***	-0.0036
	(0.0200)	(0.0263)	(0.0913)	(0.0020)	(0.0216)	(0.0279)	(0.0885)	(0.0221)	(0.0210)	(0.0272)	(0.0842)	(0.0053)
E/TA_{t-2}	-0.0255	-0.0167	0.0386	0.0003	-0.0195	-0.0410	0.0931	-0.0143	-0.0118	-0.0355	0.0677	-0.0019
	(0.0212)	(0.0286)	(0.0796)	(0.0020)	(0.0201)	(0.0288)	(0.0804)	(0.0181)	(0.0187)	(0.0302)	(0.0764)	(0.0042)
E/TA_{t-3}	0.0078	0.0319	-0.0103	-0.0019	0.0166	0.0521**	0.0520	0.0188	0.0137	0.0437	-0.0056	0.0087**
	(0.0223)	(0.0283)	(0.0766)	(0.0018)	(0.0207)	(0.0264)	(0.0697)	(0.0144)	(0.0190)	(0.0276)	(0.0774)	(0.0040)
E/TA_{total}	0.0233	-0.01740	0.3096*	0.0007	0.0205	0.0171	0.5081***	0.0299	0.0192	-0.0200	0.4425***	0.0032
	(0.0285)	(0.0412)	(0.1623)	0.0028	(0.0297)	(0.0410)	(0.1490)	(0.0245)	(0.0311)	(0.0349)	(0.1397)	(0.0069)
Ln (TA)	-0.0024	-0.0012	-0.0034	0.0003	-0.0018	-0.0036	-0.0036	-0.0031	-0.0036	-0.0014	0.0002	0.0015**
	(0.0034)	(0.0046)	(0.0110)	(0.0003)	(0.0032)	(0.0050)	(0.0101)	(0.0028)	(0.0034)	(0.0053)	(0.0101)	(0.0006)
CONC	-1.5636**	-0.6102	-0.6369	-0.0042	-1.7026***	-0.5095	-1.8517	-0.2451	-1.2766*	-0.4469	0.7280	0.1857**
	(0.7199)	(0.6203)	(2.0406)	(0.0476)	(0.7277)	(0.5597)	(2.0586)	(0.4029)	(0.7240)	(0.5681v	(2.1514)	(0.0905)
Ln(NCI)	-0.0002	-0.0031	0.0408	0.0047	-0.0147	-0.0168	0.0427	-0.0308	0.0109	-0.0094	0.1515	0.0116*
	(0.0351)	(0.0293)	(0.1197)	(0.0032)	(0.0373)	(0.0305)	(0.1120)	(0.0279)	(0.0382)	(0.0360)	(0.1489	(0.0060)

	Models where Risk =NPL/L				Models where Risk =EDF				Models where Risk = PD_{5Y}			
	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=NPL/L	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=EDF	Y=x-EFF_t	Y=τ-EFF_t	Y=E/TA_t	Y=PD_{5Y}
ID	-0.0585	-0.1157	-0.2451	-0.0033	-0.0401	-0.0855	-0.2020	0.0347	-0.0459	-0.1085	-0.3475	-0.0215
	(0.1074)	(0.1299)	(0.4086)	(0.0184)	(0.1053)	(0.1324)	(0.4091)	(0.0836)	(0.1094)	(0.1402)	(0.4449	(0.0206)
BS	-0.1435***	0.1052**	0.1996	-0.0109**	-0.1559***	0.1353***	0.1747	0.0610**	-0.1486***	0.1313***	0.1753	0.0006
	(0.0424)	(0.0444)	(0.1501)	(0.0047)	(0.0397)	(0.0491)	(0.1568)	(0.0299)	(0.0380)	(0.0508)	(0.1586)	(0.0074)
IR	1.7118***	0.3600	1.3585	-0.0748*	1.8090***	0.7173	1.3017	0.5716*	1.8559***	0.3698	0.7250	-0.0125
	(0.4082)	(0.5444)	(1.5135)	(0.0440)	(0.4154)	(0.5255)	(1.6102)	(0.3021)	(0.4280)	(0.5629)	(1.6152)	(0.0728)
GDPG	-1.1146	0.5542	2.5631	0.0054	-1.1137	0.7703	2.8478	-0.4767	-1.6362**	0.6044	1.6767	-0.1262
	(0.6984)	(0.7066)	(2.7292)	(0.0526)	(0.7346)	(0.7407)	(2.5891)	(0.7241)	(0.7698)	(0.7750)	(2.7600)	(0.1292)
GDPP	0.0322	-0.1423**	-0.1707	-0.0030	0.0288	-0.1077*	-0.2689	-0.0191	0.0407	-0.1129***	-0.1914	-0.0114
	(0.0592)	(0.0634)	(0.2243)	(0.0061)	(0.0629)	(0.0606)	(0.2258)	(0.0393)	(0.0683)	(0.0622)	(0.2069)	(0.0109)
POD	-0.0013	0.0188	0.0538	-0.0004	-0.0013	0.0215	0.0434	-0.0012	-0.0086	0.0184	0.0505	0.0018
	(0.0102)	(0.0130)	(0.0374)	(0.0007)	(0.0106)	(0.0138)	(0.0370)	(0.0071)	(0.0119)	(0.0129)	(0.0353)	(0.0022)
Sample period:	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007	1995-2007		1995-2007	1995-2007	1995-2007
Sample composition:	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks	EU25 commercial banks
Observations:	1015	1015	1015	1015	1012	1012	1012	1012	1015	1015	1015	1015
Sargan test, 2nd step, $\chi^2(148)$	143.99	162.76	154.42	162.72	159.45	167.7935	134.6961	169.67	166.00	162.88	126.034	116.5225
AB test AR(1)	-4.204***	-7.070***	-5.1022***	-5.3376***	-3.7906***	-7.4004***	-5.2307***	-6.8679***	-3.9858***	-6.9549***	-5.0226***	-6.9845***
AB test AR(2)	0.09166	0.4037	0.7703	0.3038	-1.0101	0.5092	0.6711	-0.0139	0.1265	0.3972	0.5857	1.4400

Note: We reported asymptotic standard errors in brackets. The symbols *, **, and *** represent significance levels of 10%, 5% and 1% respectively. The Sargan/Hensen test of over-identifying restrictions for the GMM estimators: the null hypothesis is that instruments used are not correlated with residuals and so the over-identifying restrictions are valid. Arellano-Bond (AB) test for serial correlation in the first-differenced residuals. The null hypothesis id that errors in the first difference regression exhibit no second order serial correlation.

Appendix. Efficiency estimation

Cost efficiency is measured using the Stochastic Frontier (SF) analysis and, namely, the Battese and Coelli's (1992) stochastic frontier model:

$\text{Ln } TC_{i,t} = \mathbf{x}_{i,t}\, \beta + (V_{i,t} + U_{i,t})$

where *t* denotes the time dimension, *ln TC$_i$* is the logarithm of the cost of production of the i-th bank, x_i is a *kx1* vector of standardised input prices and output of the i-th bank, β is a vector of unknown parameters, V_i are random variables which are assumed to be i.i.d $N(0,\sigma^2_V)$ and independent of U_i, U_i are non-negative random variables which are assumed to account for the cost inefficiency in production and are assumed to be i.i.d. as truncations at zero of the $N(\mu,\sigma_U^2)$ distribution, η is a parameter to be estimated. Following an approach similar to Altumbas et al., (2000), we use the following translog functional form[21] to estimate separate national frontiers[22]:

[21] The choice of the use of translog is motivated by two reasons. First, Altunbas and Chakravraty (2001) identified some problems associated with using the Fourier functional form, especially when dealing with heterogenous data sets. Secondly, Berger and Mester (1997) observe that the translog functional form and Fourier-flexible form are substantially equivalent from an economic viewpoint and both rank individual bank efficiency in almost the same order.

[22] Namely, we estimate the following ten frontiers: 1) Austria; 2) Belgium, Denmark, Finland, Netherlands, Sweden; 3) France; 4) Germany; 5) Italy and Malta; 6) Spain and Portugal; 7) United Kingdom and Ireland; 8) Greece, Cyprus, Bulgaria and Romania; 9) Slovenia, Hungary, Slovakia and Check Republic; 10) Poland, Lithuania, Latvia, Estonia. . Since some countries have a small number of firm-observations, we need to pool some country together. In these latter case, we use the Battese and Coelli's (1995) stochastic frontier model to account for sample heterogeneity: We also include some environmental variables (*z*) to use them for modelling the inefficiency distribution without directly including these in the production frontier in order to reduce the heterogeneity in our data set. The inefficiency components u_i are assumed to be distributed independently, but not identically. For each i-th firm the technical inefficiency effect is obtained as truncation at zero of a normal distribution $N(\mu_i, \sigma^2)$ where the mean μ_i is a function of M factors representing the firm specific environment: $\mu_i = \delta_0 + \sum_{j=1}^{5} \delta_j z_{ji}$, where GDP pro-capita (Z_1), Population density (Z_2), Short term Interest rates (Z_3), Inflation Rate(Z_4), Domestic banking industry concentration (Z_5). In this way, we assume that all bank in our sample share the same technology and environmental factors influence only the distance between each firm and the best practice. As noted Bos et al (2007 and 2009), this approach enable one to account for heterogeneity across banks and still benchmark different banks against an identical frontier. This approach has been adopted in several studies dealing with financial services industry, such as Worthington (1998), Frame and Coelli (2001), Williams (2004) and Beccalli (2004).

$$\ln TC = \alpha_0 + \sum_{i=1}^{3}\alpha_i \ln y_i + \sum_{i=1}^{3}\beta_i \ln w_i + \tau_1 \ln E + t_1 T +$$

$$+\frac{1}{2}\left[\sum_{i=1}^{3}\sum_{j=1}^{3}\delta_{ij}\ln y_i \ln y_j + \sum_{i=1}^{3}\sum_{j=1}^{3}\gamma_{ij}\ln w_i \ln w_j + \phi_1 \ln E \ln E + t_{11}T^2\right] +$$

$$+\sum_{i=1}^{3}\sum_{j=1}^{3}\rho_{ij}\ln y_i \ln w_j + \sum_{j=1}^{3}\psi_i \ln y_i \ln E + \sum_{j=1}^{3}\varphi_i \; T \ln y_i +$$

$$+\sum_{j=1}^{3}\theta_i \ln w_i \ln E + \sum_{j=1}^{3}\vartheta_i \; T \ln w_i + \ln u_c + \ln \varepsilon_c$$

where TC is the logarithm of the cost of production, y_i (i = 1, 2, 3) are output quantities, w_j (j = 1, 2, 3) are input prices, k_i (i = 1, 2, ..., 6) are bank specific factor influencing the efficiency estimation, ln E is the natural logarithm of total equity capital, T is the time trend, u_c are the cost inefficiency components. In order guarantee the linear homogeneity in factor prices (i.e. $\sum_{j=1}^{3}\beta_j = 1$; $\sum_{i=1}^{3}\gamma_{ij} = 0$ and $\sum_{j=1}^{3}\rho_{ij} = 0$), it is necessary (and sufficient) to apply the following restrictions: 1) the standard symmetry: according with this restriction, it is assumed that $\delta_{ij} = \delta_{ji}$ and $\gamma_{ij} = \gamma_{ji}$; 2) linear restriction of the cost function.

Bank inputs and outputs are defined according to the value-added approach, originally proposed by Berger and Humphrey (1992). We posit that labour, physical capital and financial capital are inputs[23], whereas demand deposits (y_1), total loans (y_2) and other earning assets (y_3) are outputs[24]. We also estimate the alternative revenue efficiency measures: in this "alternative"

[23] Input prices are obtained as total personnel expenses over total assets (w_1) , total depreciation and other capital expenses over total fixed assets (w_2) and total interest rate expenses over total funds (w_3).

[24] This selection of inputs and outputs follows the studies by Sathye (2001) and Dietsch and Lozano (2000), Aly et al. (1990) and Hancock (1986), wherein the author develops a methodology based on user costs to determine the outputs and inputs of a banking firm. Although off-balance sheet (OBS) items may play a role in generating bank value-added, we omit to consider OBS items since our sample also includes small banks that do not have OBS items or data are not available in the Bankscope database. By including the OBS in the output selection, the sample size would have been substantially reduced, especially because we use a AR(3) process in model (1).

approach, banks take input and output quantities as given and we selected these measures since prices are often inaccurately measured in banking[25]. The revenue efficiency is estimated using the same translog functional model adopted for the cost efficiency, by using as dependent variable the total bank's revenue in the revenue function. The Bank input and output definition adopted is the same adopted to estimate the cost efficiency.

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[25] Berger and Mester (1997, p. 904) notes that "if prices are inaccurately measured –as is likely, given the available banking data – the predicted part of the standard profit function would explain less of the variance of profits and yield more error in the estimation of the efficiency terms $ln\ u_\pi$. In this event, it may be appropriate to try specifying other variables in the profit function that might yield a better fit, such as the output quantity vector, y, as in the alternative profit function".